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Theorem 4.11 (Chebyshev's Theorem) The probability that any random variable X will assume a value within k standard deviations of the mean μ is at least $1-1/k^2$. That is,

$$P(\mu - k\sigma < X < \mu + k\sigma) \ge 1 - \frac{1}{k^2}.$$

The theorem gives a conservative estimate of the probability that a random variable assumes a value within k standard deviations of its mean for any real number k.

PROOF (only for continuous case)

By our previous definition of the variance of X we can write

$$\sigma^{2} = E[(X - \mu)^{2}]$$

$$= \int_{-\infty}^{\infty} (x - \mu)^{2} f(x) dx$$

$$= \int_{-\infty}^{\mu - k\sigma} (x - \mu)^{2} f(x) dx + \int_{\mu - k\sigma}^{\mu + k\sigma} (x - \mu)^{2} f(x) dx$$

$$+ \int_{\mu + k\sigma}^{\infty} (x - \mu)^{2} f(x) dx$$

$$\geq \int_{-\infty}^{\mu - k\sigma} (x - \mu)^{2} f(x) dx + \int_{\mu + k\sigma}^{\infty} (x - \mu)^{2} f(x) dx$$

since the second of the three integrals is nonnegative. Now, since $|x-\mu| \geq k\sigma$ wherever $x \geq \mu + k\sigma$ or $x \leq \mu - k\sigma$, we have $(x-\mu)^2 \geq k^2\sigma^2$ in both remaining integral. It follows that

$$\sigma^2 \ge \int_{-\infty}^{\mu - k\sigma} k^2 \sigma^2 f(x) dx + \int_{\mu + k\sigma}^{\infty} k^2 \sigma^2 f(x) dx$$

and that

$$\frac{1}{k^2} \ge \int_{-\infty}^{\mu - k\sigma} f(x) dx + \int_{\mu + k\sigma}^{\infty} f(x) dx$$

Hence

$$P(\mu - k\sigma < X < \mu + k\sigma) \ge 1 - \frac{1}{k^2}.$$

For k=2 the theorem states that 3/4 or more of the observations of any distribution lie in the interval $\mu \pm 2\sigma$.

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Example 4.22 A random variable X has a mean $\mu=8$, a variance $\sigma^2=9$, and an unknown probability distribution. Find (a) P(-4 < X < 20), (b) P(|X-8| > 6)

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Solution.....

$$P(-4 < X < 20) \ge \frac{15}{16}, \qquad P(|X - 8| \ge 6) \le \frac{1}{4}.$$

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Only when the probability distribution is known can we determine exact probabilities.